Emotion Detection and Student Engagement in Distance Learning During Containment Due to the COVID-19

Benyoussef ABDELLAOUI [1]* iD ✉ , **Ahmed REMAIDA** [1] iD ✉ , **Zineb SABRI** [2] iD ✉, **Younes EL BOUZEKRI EL IDRISSI** [1] iD ✉ , **Aniss MOUMEN** [1] iD ✉

[1] Laboratory of Engineering Sciences, National School of Applied Sciences, Ibn Tofaïl University, Kenitra, Morocco.
[2] Faculty of Sciences, Laboratory of Computer Science, Ibn Tofaïl University, Kenitra, Morocco
*Corresponding Author.

Abstract

Distance learning is one of the teaching and learning approaches adopted after the COVID-19 pandemic. The task of getting learners interested in class is difficult for the professors. In this research, a mechanism has been developed to estimate student engagement levels and emotions. Visual data from recorded videos of students participating in learning courses are utilized due to the availability of multiple methods for measuring student engagement levels. The data from the videos recorded and sent by students is processed to determine the extent of student engagement and identify their emotions. The system has been implemented and tested, enabling the evaluation of student attention. Several algorithms and techniques have been used to implement our prototype as CNN. A private dataset has been created to train and evaluate the model. The results show that it is possible to measure participation, learn about feelings, and use them to make decisions in favor of student outcomes and improve teaching and learning methods. This technology can be applied in other scenes, such as self-driving and security, with a minor adjustment.

Keywords: Convolutional Neural Network (CNN); COVID-19; Distance learning; Emotion detection; E-learning; Student engagement.

Introduction

Many institutions adopted distance learning after the spread of the COVID-19 pandemic. Because they are used to lecturing in classes, teachers now find themselves in an unfamiliar and challenging environment. Teachers find it difficult to determine the degree of engagement of their students. Teachers must ensure student engagement, develop a sense of community, and facilitate communication and collaboration. To get the best results, not only must the teacher ensure that students are focused, feel confident and comfortable, interact online, and follow their work, but also collect their feedback easily from online classes. So, the task is much more complex, and it is also necessary to think about the logistic dimension and the working platforms [1].

Various forms of distance learning can be identified, like peer-assisted learning, self-directed learning, and collaborative learning [2]. To reach this goal, faculty members should develop their techno-

pedagogical skills and combine learning techniques to support student engagement because it is also vital for the fundamental process of learning[3].

Student engagement is defined as the energy and time devoted by the student to doing activities. It influences the learning process, motivates students to advance their critical reasoning skills, and promotes persistence[4].

In this paper, the first aspect of the research question will be described, focusing on estimating the levels of engagement with the video recording of the course during a distance learning session in the context of the COVID-19 period. The second aspect is the estimation of the student's emotional state.

The rest of the publication is structured as described below. Section two examines and analyses several significant articles on student engagement. Section three addresses facial recognition and online learning; Section four details the strategy for our study experiment; Section five presents the experiment's findings; Section six discusses the results and research constraints; and Section seven summarizes the study's key findings.

Student engagement

The literature review does not provide a single definition of student engagement. Ali et al [5] state some empirical-based definitions of engagement. Also, the roots of the term "Student engagement" are widely used in national surveys on student engagement conducted by researchers in North America and Australia in 2008. According to the authors, "student involvement" refers to the time and energy invested by both institutions and students to foster student achievement and the institutions' positive reputation.

Alexander Astin is among the first researchers who introduced student engagement, particularly in [6]; the article presents a theory of student development based on student involvement. The overall goal is to ameliorate both teaching and learning in the establishment of higher education. Much of the later research has shown that the profound relationship between student engagement accompanied by persistence and social engagement leads directly to student success and development. Student involvement has a favorable impact on teaching quality and academic success [7]. Some researchers are trying to define the opposite of engagement. An unengaged student is unwilling to change his or her ways and does not see that he or she has an

interlocking of individual interests, goals, and aspirations with learning communities [5]. There are three types of engagement in the literature: behavioral, emotional, and cognitive engagement [8]. Behavioral engagement is the adherence to and pursuit of behavioral norms, such as attendance, participation, giving effort, persistence, focus, attention, asking questions, contributing to class discussion, and rejecting disruptive or harmful behavior [9]. Attitude and feelings are connected to emotional engagement. It is the occurrence of emotive reactions such as curiosity, pleasure, or a sense of affiliation and belonging [8]. As defined by Ladino Nocua AC et al [10], cognitive engagement refers to students' commitment and intensity of psychological investment in their learning, seeking to overcome the challenging obstacles and barriers to learning and task completion. For example, Self-regulated learning is considered a kind of cognitive engagement. In his review of literature [5], Ali Manisah and Hassan assert that the foci of student engagement can be divided into three axes: First, the aspect of individual student learning, taking into consideration attention, interest, and active participation in learning.

Secondly, the structural role or collaborative process of student engagement includes other roles of a student as trustee, delegate, and student member and committee representation. They are finally developing a sense of belonging for each student and how to engage marginalized groups on the value of representation in transmitting identity. In some universities, the concentration does not focus on all axes [11]. Many authors have proposed several typologies of student engagement that are useful for a better understanding of the engagement types, like the work of Hamish Coates [12]. As shown in Fig 1, the engagement typology is organized around two axes, social and academic. Many styles make up this typology. There were four different kinds of students in this structure: Students who actively engage in their learning environment, students who value the social aspects of interacting with staff and other students, students who support collaborative work with other students inside or outside of the classroom in a less socially oriented way, and students who engage passively avoid taking part in routine activities.
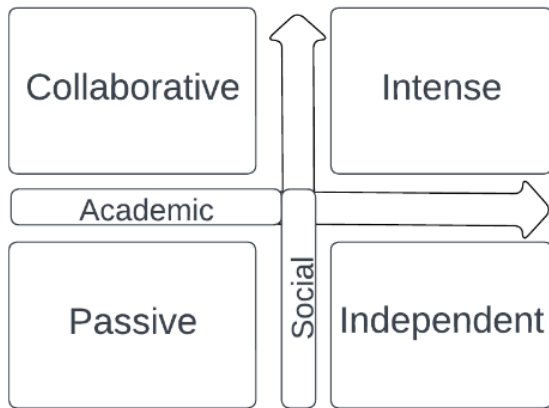
Figure 1. Styles of student engagement [12].

The reasons to get students engaged are to improve learning, pass and maintain levels, establish equality and social justice, commit to the importance of the program as well as the institutional benefits.

Levels of student engagement

Many researchers suggested levels to categorize students based on their engagement stage. Altuwairqi [13] summarized current engagement levels and proposed a new one.

Table 1. Current levels of engagement in the literature.

Papers	Year	Levels	Label of levels
Schlechty P C [14]	2011	5	Engagement, Strategic compliance, Ritual compliance, Retreatism, Rebellion
D'Mello S, Graesser A[15]	2011	4	Productive confusion, Disequilibrium, hopeless confusion, Disengagement
Whitehill J, Serpell Z [16]	2014	4	Very engaged, engaged in a task, nominally engaged, not engaged
Jang M, Park C [17]	2014	2	Engaged, not engaged
Li J, et al [18]	2016	3	High Attention, Medium attention, Low attention
Monkaresi H, et al [19]	2017	2	Engaged, not engaged
Altuwairqi K, et al [13]	2018	5	Strong engagement, high engagement, medium engagement, low engagement, disengagement

Distance learning and emotion recognition

There are several definitions of distance learning or distance education. This kind of learning can be free or paid, covering several denominations such as e-learning, open training, MOOC (Massive Open Online Course), and virtual campus…. Each course is conducted outside the typical classroom, uses unique resources, does not have a teacher in attendance, and is built on a multidisciplinary learning model. In addition, the course is multidisciplinary and varied, involving a large group of students according to their requirements and time availability while making the learner responsible for their progress [20]. The learning resources are available to the student with little intervention from the teacher. This freedom to manipulate the materials encourages students to enjoy their education and enhances their progress. Distance learning during COVID-19 poses many problems for teachers in getting students' feedback,

emotions, and evaluation. Thus, the transmission channel is usually a dedicated platform for distance learning. In the case of video transmission, the knowledge of their emotional state, the level of knowledge acquisition, and their involvement can be reflected in their video. In literature, several methods exist for analyzing and extracting emotions from images. For example, this work indicates a popular feature extraction method [21]. This work [22] justifies the existence of an emotional-cognitive connection that significantly impacts how students behave. Several datasets are now available for researchers to perform automatic facial expression recognition (FER) implementing deep learning [23].

A person's emotional state is familiar in many scientific fields, such as image processing, signal processing, robotics, and human-machine interaction. The emotional state can be obtained through several behavioral signs and auditory and physiological signals of emotion. Body language

and facial expressions are good visual clues to the emotional state. The processing of noiseless speech signals ensures an estimation of the emotional state. Autonomic nervous system (ANS) activity is a reliable tool that gives a more accurate view of the subject. The recording and analysis of linked physiological information are used to analyze activity concerning emotional state [24].

Materials and Methods

Methods

Participants

In our experiment, students attending the online course will record their screens and faces during the entire course. The students are aware of the purpose of the recording and have given their full consent for further processing in a purely academic context. Figure 2 shows the data collection method. The participants in this study are part of the national school of applied sciences of the IBN Tofaïl University of Kenitra in Morocco. The participants are from the electrical engineering group (50 students), the industrial engineering group (16 students), and the compilation group (15 students). So, the total number of participants in our current study is 45.
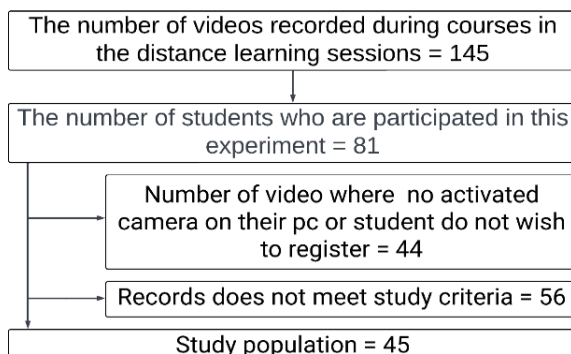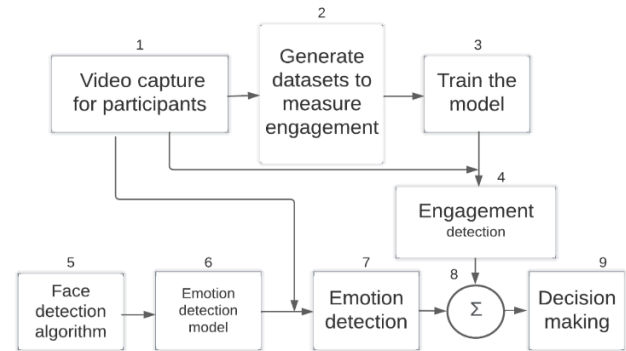

Figure 2. The participants' organization chart.

Collection of data

After participating in the course via the Google Meet platform, students are given a link on google drive to utilize for sending the session report, the source code for the practical work, and other tasks they have completed during the session. The collection method was first tested on a few students to make corrections and adjust the experimental protocol.

Figure 3. Flowchart of our work.

The vital data collected includes videos of various sizes, quality, and duration. Additionally, numerous comments are posted by students and lecturers on the platform. The researchers of this paper utilize Google Colab as the training platform, and Python is employed, utilizing various packages such as TensorFlow, Scikit Learn, Pandas, Numpy, Matplotlib, Seaborn, etc. The flowchart is elaborated in Fig 3 as follows:

Step one: During the online courses, participants can decide whether or not to record and share their movies. The moderator alerts the audience that sessions are being recorded and agrees to any possible processing of the sessions for purely academic and research purposes.

Step two: A dataset consisting of multiple photos was constructed by decomposing the session recording into images. Engagement classification algorithms will be utilized on this dataset, relying on the extracted face data. The Haar cascade algorithm has served as the foundation for our dataset. The Haar cascades are a machine-learning object detection algorithm. This algorithm, detailed in [25], is based on four essential steps: The selection of Haar-like features, create an integral image, the execution of the AdaBoost training, and the creation of classifier cascades. Our private dataset was

created by detecting the face and tracking eye movement in student recording frames.

Step three: The dataset is then trained using deep learning techniques to build a CNN (Convolutional neural network), a model capable of predicting engagement from an image or video.

Step four: For each input, the model can predict the level of engagement.

Steps five and six: Another CNN model of emotion prediction is constructed for each frame in the video utilized in the student engagement experiment.

Step seven: The same data processed by the engagement model will be processed to determine the level of emotions.

Results and Discussion

Results

The only way to communicate between the teacher and their students was by using platforms that allowed virtual meetings and the exchange of resources. In this paper, the features of the platform have been described.

According to Elshami et al[2] which describes the factors that influence student engagement in learning, several elements are involved in the engagement strategy. Initially, the elements of the overall process of online sessions are examined. Officially, students have institutional accounts offered by the university and can access many of the services associated with those accounts, but students use other virtual rooms to communicate further. For each course, students have a classroom where they can find an integrated and accessible electronic portfolio. The teacher manages the classroom, leading the training with collaborators. The teacher begins the session, and students may take the floor anytime. If necessary, the teacher can mute all participants. (Item 5) Each student has a PC or smartphone and can view the resources needed to follow the course. (Item 6) The platform is flexible. In live sessions, students can comment by text and participate by audio or video after the moderator's approval. Students are free to post any file in the appropriate folder. (Item 7) During a

Steps eight and nine: The combination of the two model outputs is utilized for student clustering and determining the status of individual learners.

The description of the data collected during our experience

The size of the recorded videos is from 180 MB to 9 GB. The quality of the videos varies from 360p to 720p. The duration of the videos can vary from 10 min to 3h30min, which is different because the students find difficulties in the recording, which implies these differences in quality, duration, and size. Python programming is used for video processing, with Google Colab as the execution platform. Our choice to use this platform comes from needing more resources concerning the RAM and the GPU; moreover, it is free.

student's presentation, others can interact asynchronously or synchronously in a fluid way. (Item 8) The platform provides collaborative work, so students can work together on case studies, carry out projects, write reports, etc. (Item 9) Students can conduct group evaluations of their classmates' work. (Item 10) Students are not required to evaluate the personal performance of their colleagues. (Item 11) Students post their names and sometimes even their pictures on their profiles, making it easy for the teacher to identify students by name. (Item 12) The training institution and the academic staff provide e-mail announcements or reminders to students. (Item 13) The teacher and students can smoothly contact each other via e-mail in private or public mode on the resource platform to ask questions about the course or other topics. (Item 14) The teacher announces the activity's objectives to the students at the beginning of the online session. (Item 15) The deadline is always known when the teacher gives the assignment to be handed in. (Item 17) The teacher gives recommendations by e-mail or announcements. (Item 19) The teacher usually presents the rating scale during the assessments. (Item 20) During a synchronous session, the teacher varies the modalities of interaction with students by using presentations in ppt, video, text, audio, etc. (Item 21) The resources made available to students are

subject to feedback by them through various methods such as audio, text, e-mail, etc. (Item 22) In addition to the resources provided; students deepen their knowledge through online research references. (Item 23) Classroom events and guest speakers are hosted via a synchronous web conference. (Item 24) The understanding of the content begins from the simple to the complex. (Item 25) The work assigned to the students is presented online and then sent to the teacher for evaluation. (Item 26) Students search for resources according to their chosen theme. (Item 27) Project-based studies are essential, and the teacher assigns homework to the students to reflect on and learn. (Item 28) In authentic learning situations, project-based and team-based learning methods, such as practical work. (Item 29) Students are evaluated by the teacher or sometimes by the students themselves.

The exclusive method of communication between the teacher and students involved utilizing virtual meeting platforms and resource sharing. This paper elaborates on the functionalities of these platforms. It is strongly advised that each institution develops its own platform hosted within the same country to safeguard information confidentiality and prevent service interruptions caused by political or military conflicts, like wars. The platform must be given absolute priority. Our study found that multiple institutes use platforms that aren't conforming to the criteria, such as data security, performance, and reliability.

Face tracking engine, engagement-detection, and model classification results

Face detection is a specific application of object detection that focuses on identifying and localizing human faces within images or video frames. It is a binary classification problem coupled with a localization problem, and it is used in many applications, such as security and person recognition. The algorithm proposed in 2001 by Paul Viola and Michael Jones aims to solve the face detection problem. This algorithm consists of scanning an image converted to a grey level by sliding windows to calculate some of the features to have the integral image j(x,y) given in Eq 1.

$$j(x, y) = \sum_{x' < x, \, y' < y} i(x', y') \qquad 1$$

$$I(i, j) = \begin{cases} 255 & if \; J(i,j) > s \\ 0 & otherwise \end{cases} \qquad 2$$

The result given by our system for the thresholding image is given in **Error! Reference source not found.** 4 -c.
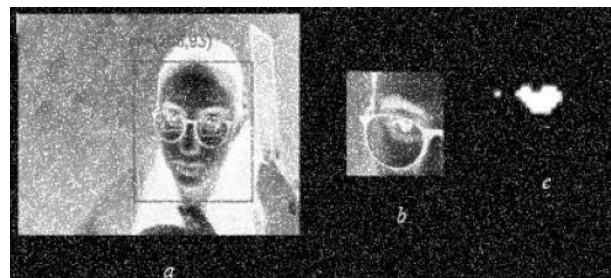

Figure 4: a-Face tracking, b: Eye detection, and c: Thresholding image.

The followingFigure shows the output of our model when the face is not in the frontal position, and the eyes are closed.

Figure 5. No face or eyes were detected.

Based on this treatment, our dataset is defined as comprising two folders. One comprises images labeled "engaged", and the other is "not engaged". The engaged state is defined as follows: The student is in front and looks directly into the screen, and the eyes are open; the other state, not engaged, is defined as follows the student looks to the right or the left or the eyes are closed. Then, the dataset was used to train a model that can predict whether someone is engaged or not.

Figure 6 shows our system's training and validation accuracy and training and validation loss.
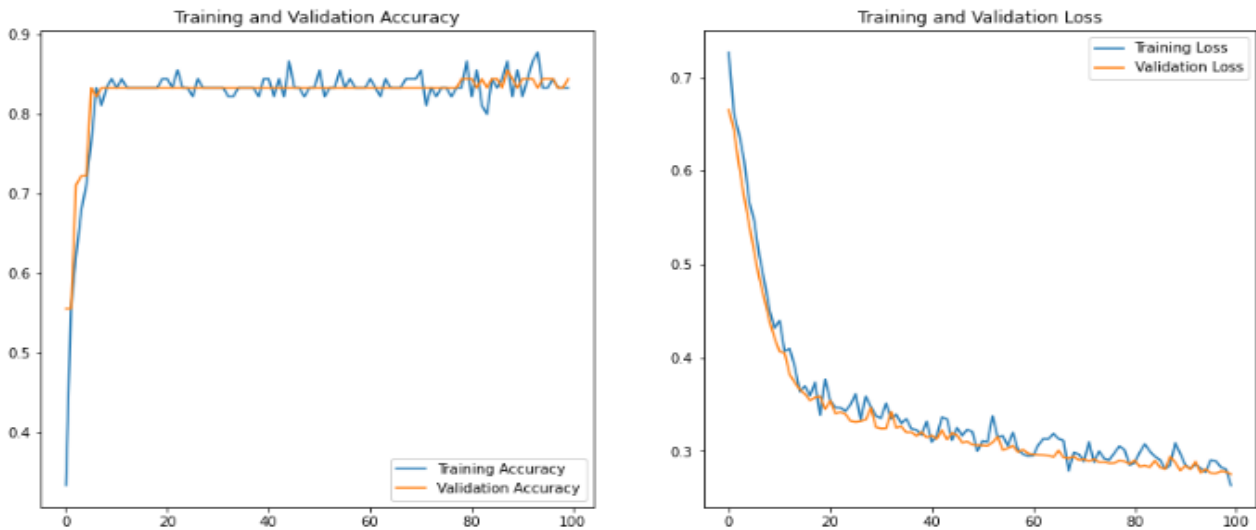
Figure 6. Our system's training and validation accuracy and training and validation loss

Engagement is measured in many ways, using quantitative self-assessment, qualitative, observational, and other methods [26]. Our work used the Monsonkri model, which consists of two models. Figure shows the distribution histogram of the engagement (number 2) and disengagement (number 1) states of students who participated in our experiment during a 2.5-hour course.
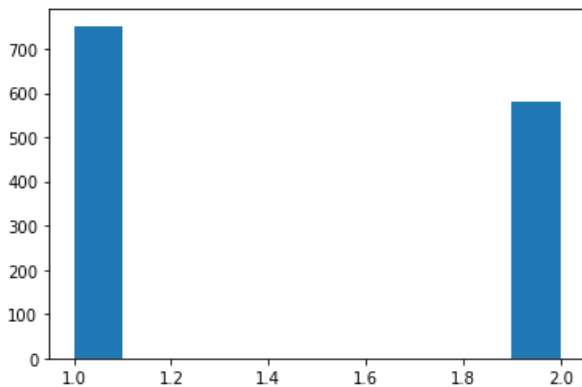

Figure 7. Histogram of engaged state (number2) and not engaged state (number1).

Table 2 shows the different statistical values for that student and that the most dominant feeling is the neutral feeling (mean column), with a score of 0.576. The weakest sentiment is disgust. The table also shows that the student experienced all the feelings without exception getting a score above 0.8. In addition to the neutral state, sadness is a feeling that should not be overlooked, followed by anger. In practice, other feelings do not count for much. The mode column is the value that appears

The student is engaged more than 42% of the time.

Model of emotion classification

The emotion system has been implemented, comprising six core emotions: anger, disgust, fear, happiness, sadness, surprise, and the neutral state. This categorization is widespread in the literature that is interested in the study of emotions. The FER Library was utilized for conducting facial recognition of emotions. The decomposition of the video recording during a student's online session resulted in 3593 frames. Our system determined the emotions during the whole session.

most often. The min, max, median, variance, stdev, pstdev, pvar, and Har column mean returns the most minor, the most extensive, middle, variance, standard deviation, the population standard deviation, the variance of the whole distribution, and the harmonic average (central position) value for each sentiment respectively. **Figure** illustrates the mean of all feelings experienced by the student during the learning process in an online session.
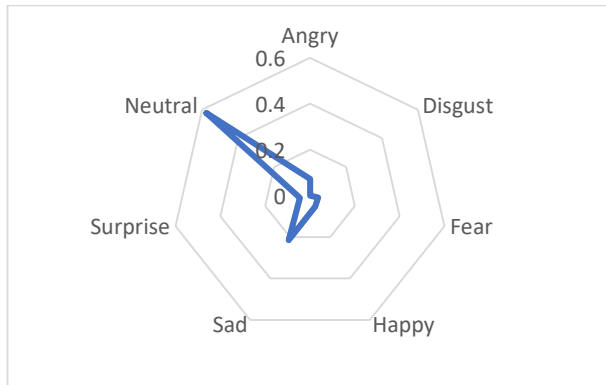
Figure 8. The mean of each feeling in the video.

The following table provides a statistical description of the video analysis.

Table 2. Statistic table of five emotions in the video.

Feeling	Mode	Min	Max	Mean	Median	Variance	Stdev	Har mean
Angry	0.01	0.0	0.75	0.072	0.05	0.006	0.078	0
Disgust	0.0	0.0	0.03	3.06 e-05	0.0	4.723 e-07	0.0006	0
Fear	0.01	0.0	0.8	0.036	0.02	0.002	0.050	0
Happy	0.0	0.0	0.99	0.053	0.01	0.012	0.112	0
Sad	0.04	0.0	0.9	0.214	0.14	0.036	0.190	0
Surprise	0.01	0.0	0.96	0.045	0.01	0.012	0.110	0
Neutral	0.82	0.01	0.98	0.576	0.65	0.069	0.264	0.330

Stdev= Standard deviation, Pstdev = The population standard deviation, Pvar = The variance of the whole distribution, and Har mean = The harmonic average.

The min value and the max value in the given table are the smallest value and the most outstanding value in the data. The mode in arithmetic can be discovered by sorting the data and then identifying which value appears the most frequently. The median is the middle value when the data is sorted in ascending or descending order. The arithmetic mean denoted $\bar{x}$ equals the total of all observations divided by N, all observations. Its formula is $\frac{1}{N}\sum_{i=1}^{n}x_i$. As known, the fundamental drawback of mean arithmetic is that excessive numbers influence it. The sample standard deviation formula is: $\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{x})^2}$ Where x_i represents the probability value for given emotion in frame i, the standard deviation measures a set's dispersion or variability from its mean. It measures how far apart the data are from the average. A more significant standard deviation suggests greater variability, whereas a more minor standard deviation indicates less variability. The population standard deviation, denoted σ, is a statistical measure that represents the amount of variability or dispersion of a population's

data from the population mean; its formula is $\sqrt{\frac{1}{N}\sum_{i=1}^{n}(x_i-\bar{x})^2}$. A more significant standard deviation means the data points are more spread out from the mean, whereas a minor standard deviation shows that the data points are closer to the mean. The formula for variance is: $\left(\frac{1}{N}\right)\sum_{i=1}^{N}(x_i-\bar{x})^2$, the measure of variance describes the spread or dispersion of a set of data points around their mean. It indicates how far the individual data points differ from the mean. The harmonic mean is commonly used to calculate average rates of change. Moreover, the reciprocal of the arithmetic mean of the reciprocals of a particular set of observations is the harmonic mean. Its formula is $\frac{N}{\sum_{i=1}^{n}\frac{1}{x_i}}$.

The following curves From Figure 9 to Figure 5 represent the emotions recorded during the video of 3593 frames for the same student. It can be stated that the student exhibits no signs of anxiety, but there are occasional brief increases in anger. In the curve of the angry state shown in Figure 9: In all

frames, the mode is 0.01. That means this value appears frequently. The mean is about 0.072. the median value is minimal. The harmonic mean is null because smaller values are more weighted than large ones. So while the data set has a few small and some large values, the harmonic mean will be closer to the small values and smaller than the arithmetic mean. A low standard deviation indicates that the data values are clustered closely around the mean.
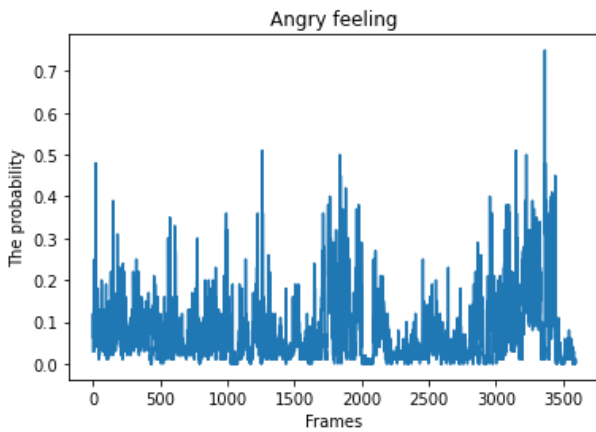

Figure 9. The curve shows the angry emotion's history.

According to Fig 10, a conclusion can be drawn that the student does not feel disgusted and lacks any visual indication. The most common value, the minimum, and the median values are 0.0, with a max of 0.03. The average value and variance are small, near zero, indicating that the data points are grouped tightly around the mean. The standard deviation has a small value indicating no spread of the data points far from the mean. Finally, the harmonic mean is 0, indicating that the average of the data points' reciprocals is 0.
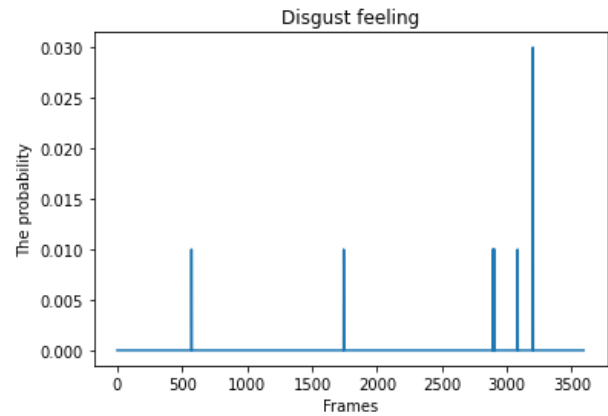

Figure 10. The curve shows the disgust emotion's history.

The fear state Fig 11 is practically null. The distribution of the fear state is positively skewed, with most values around 0.01 (mode) and a few higher values pushing the maximum to 0.8. The mean (0.036) exceeds the median (0.02), confirming the skewness. The variance (0.002) and standard deviation (0.05) suggest that the data is dispersed around the mean in a reasonably narrow range. The harmonic mean (0) shows that the data has at least one zero value, significantly impacting the total computation. There is a definite peak in the middle of the session.
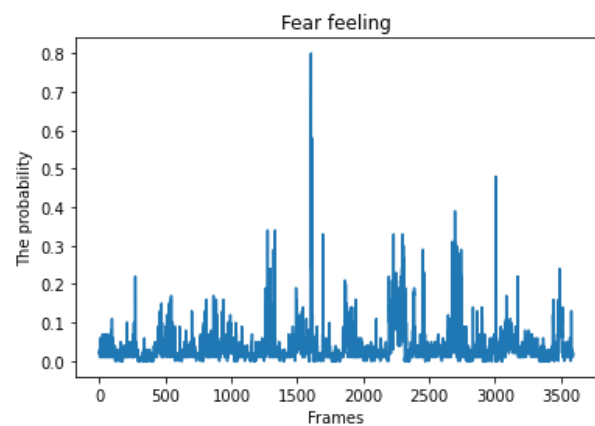

Figure 1. The curve shows the fear emotion's history.

The emotional state of happiness, as illustrated in Fig 12, is not readily apparent. There are some moments toward the end of the session. The given data shows a positively skewed distribution, with the mode and median at a small value close to 0,

indicating that most values are clustered around 0. The mean value is slightly higher at 0.053, indicating the presence of some moments of joy at the end of the course. The maximum value is 0.99, indicating a short, intense moment of excitement during the session. The variance and standard deviation are relatively low, indicating that the data points are clustered closely together. The harmonic mean is 0, indicating that the session contains at least one value of no joy expressed, significantly impacting the harmonic mean.
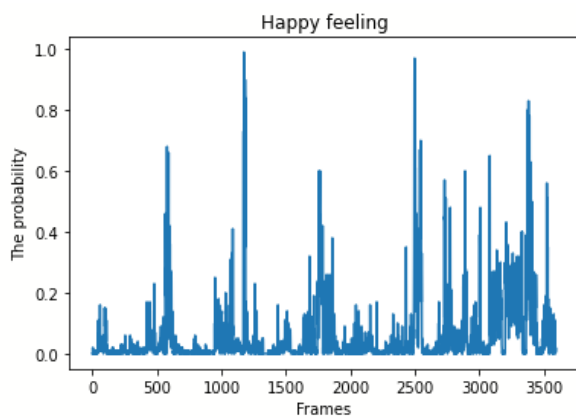

Figure 2. The curve shows the happy emotion's history.

The feeling of sadness occurs during the session; it is somewhat similar to the state of anger but more acute. A few of the statistical characteristics of this situation are discussed visually in Fig 13. The mode value is 0.04. The minimum value in the dataset is 0, and the maximum is 0.9, indicating a momentary occurrence of sadness and the absence of it. The mean value is 0.214, demonstrating that sadness is present for the student. The median value is 0.14 showing that the probabilities of sadness are slightly skewed to the right. The variance, which equals 0.036, displays how widely apart the data points are from the mean. The standard deviation is the square root of the variance, and its value is 0.19. The harmonic mean, a sort of average that accentuates the impact of smaller numbers, is 0.
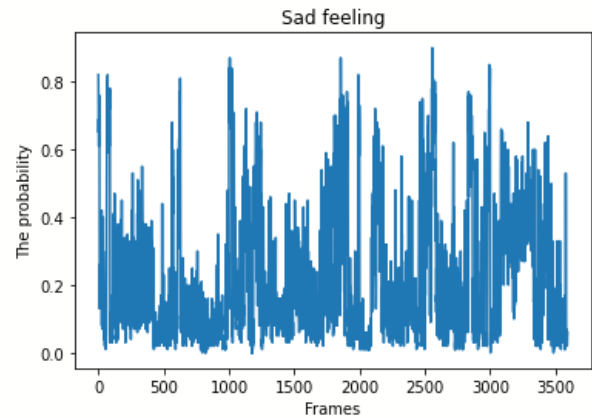

Figure 3. The curve shows the sad emotion's history.

As shown in Fig 14, the surprise state has a mode of 0.01, meaning that the student is mostly not surprised. The minimum value is 0, and the maximum is 0.96. The mean is 0.045, indicating a relatively low overall value. The median is 0.01, and the variance is 0.012. The standard deviation is 0.11, suggesting that the probabilities for sadness are spread out from the mean. The harmonic mean is 0, indicating that some shallow values of no surprise state are pulling the overall value down. The feeling of surprise is somewhat like the anger state but with several peaks. Both occur with a low probability value.
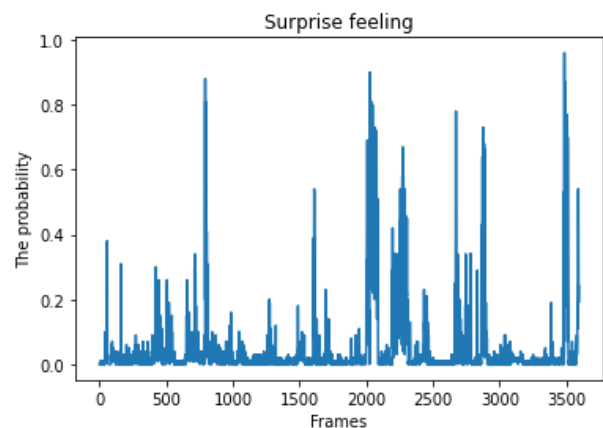

Figure 4. The curve shows the surprise emotion's history.

In the surprise feeling, graphed in Figure 5, the mode is 0.82, which means that it is the most observed emotion in the student. The minimum value is 0.01, and the maximum value is 0.98

indicating the student is showing a neutral state and absence of it. The mean is 0.576, and the median is 0.65, which indicates a slightly skewed distribution. The variance is 0.069, and the standard deviation is 0.264, which means the data has moderate variability. The harmonic mean is 0.33, which indicates a small probability for this state during the course. The neutral feeling is the most dominant state with high probability values. In conclusion, This feeling of neutrality and all the other feelings that were present but were more uncommon encapsulated this student's sentiments during the session.
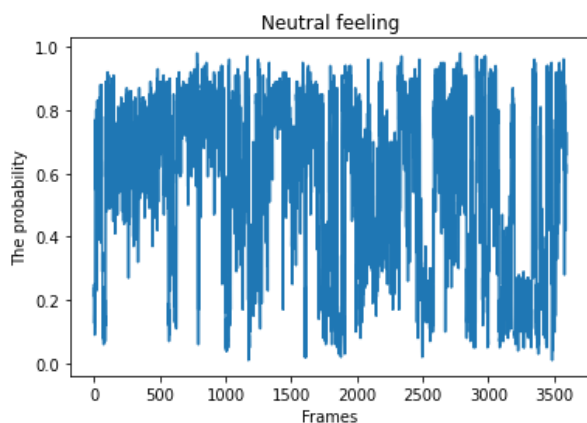

Figure 5. The curve shows the neutral emotion's history.

Discussion

In our experience, a more widespread technique that uses fewer resources was the haar cascade classifier using OpenCV to identify the face and the eyes. However, other methods, such as MediaPipe or dlib library, are more developed and achieve the same task.

For each frame, our system can determine the area of interest. The face and the eyes allow us to determine the direction in which the student points his eyes. Sometimes, the system cannot determine the face and the eyes, even if it is apparent. This weakness finds its explanation in the large inclination of the face, and perhaps the model has not trained on this type of inclination. Our experience has yielded an average student engagement of 40%. This level of engagement is

justified by the fact that the model is very selective, and the student is not a machine or a robot, so he/she is not entirely fixed on the screen for an extended period. Even if the level of engagement is not high, it does not reflect students' interest in their lessons. In our opinion, the approach should be improved, have multiple levels, and not use a binary engagement ranking.

As a limitation of the study, various issues were not addressed, including identifying the presentation type, predicting users' personalities, detecting the distance between the student and the PC screen, etc.

In literature, engagement is classified into three types (behavioral, emotional, and cognitive). In our article, The focus was limited to the affective behavioral component, specifically centered around the face and eyes, on the other hand, to the emotional engagement defined by Karimah et al [27]. The cognitive engagement part needs to be treated. This part can be processed from the log files generated by the distance learning platform. This task can be taken up in future work.

This article does not cover engagement classified as human-robot interaction [28].

The courses provided can be textual, graphic, or hybrid. Some works in the literature deal with this subject; for example, this article is cited [29]. Personality traits are a subject that attracts the attention of researchers; In this essay [30], Several publications addressing this issue have been cited. Another area of research in e-learning [31] that can improve student engagement is the introduction of serious games during teaching activities. In our future work, the intention is to examine students' posts acquired via the online learning platform to forecast their personalities, as done in [32].

Our motivation for conducting this work is to improve the quality of learning and teaching in higher education institutions. However, there are many challenges related to this work, especially when this work was done during the period of the COVID-19 pandemic, which started in late 2019 and continues to harm millions of people around the planet [33]. The disease's danger has prompted heightened collaboration and scientific research promotion. This topic of COVID-19 has been

approached from various angles, including health, education, well-being, social and human behavioral [34], and more. Studies examine how the pandemic affects people psychologically and mentally [35], sociologically, and economically [36, 37]. In the interests of everyone, individuals practice social distancing. In the establishment of education, the courses are delivered remotely through specialized platforms. At this stage, two main things should be present to join the courses: end devices and the internet. Students use their end devices, also known as an endpoint, to interact directly to access and utilize network services and applications. All communication in class occurs on end devices with internet access. The end devices used in this experiment include personal computers (PCs): desktop computers, laptops, and mobile devices such as smartphones and tablets. They are used to web browsing, creating content, communicating, and running software applications. According to Figure 6, not everyone has access to the internet (statistics provided by Morocco's finance ministry). So, in that case, absenteeism from lessons could be justified regardless of other problems due to a lack of necessary resources.
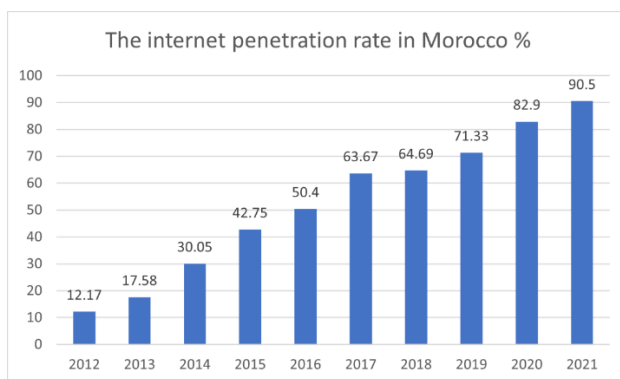

Figure 6: The Internet penetration rate in Morocco.

Students often use an Access Point (AP) using ethernet, Wi-Fi, or cellular connectivity to establish connections with routers, switches, and servers. It bridges wireless devices and the wired network infrastructure, enabling wireless communication and access to network resources. The administration, teachers, and students generate a lot of data. It is possible to assert that one is in a Big

Data context due to the continual growth of data daily. In this situation, the amount of data produced will be treated and secured. So, our subject of engagement and emotion is linked to various areas of academic research. The connection to a filar network raises security concerns. The security of data is a highly complex topic. Each student is responsible for inputting, uploading, and storing his user data, and the hosting party manages platform data. This topic is sensitive to several privacy and security vulnerabilities, just as other data transfer-related topics like 5G, the internet of things, etc [38,39]. The communication network should be protected from attacks like Man-in-the-middle, as discussed in this article [40]. The attackers might actively delay or remove the content of data received during a discussion. Stakeholders and managers in the education sector and higher education institutions will need to invest in building a structure that ensures storage, processing, computation, and security. In other words, a frog computing infrastructure is not based in another country, which improves security, privacy, and digital sovereignty.

As a conclusion of this discussion, the suggested mechanism in this publication differs from earlier approaches in that it uses visual data from recorded videos to determine student involvement levels and emotions. While there are several methods for measuring student involvement, this mechanism relies on visual clues captured in video recordings. Student engagement is usually measured using self-reporting tactics such as questionnaires or surveys, which rely on students' subjective responses. Other methods may use behavioral data such as interaction patterns, clickstream data, or physiological indications such as heart rate variability. Our proposed mechanism outperforms other methods by collecting non-intrusive data, unlike traditional methods that require direct interaction or self-reporting from students [41], leveraging rich visual information, enabling fine-grained analysis, ensuring scalability and automation, and facilitating real-time feedback. Four recently published papers that focus on emotion and engagement are referenced to compare with other works. First, article [42] presented a system built on deep-learning algorithms such as VGG-19 and ResNet-50 for facial emotion recognition and

the facial landmark approach for eye-blinking and head movement detection. Then, in this work [43], physiological data are evaluated using an LSTM-based deep learning model to recognize distinct emotions. Next, this research [44] proposes building a CNN and equipping it with residual connections to increase the network's learning rate and

classification on three Indian datasets that primarily work on classroom engagement models. Lastly, the purpose of this research [45] is to investigate the achievable of detecting student emotions by analyzing their self-written essays. Detecting student emotions in e-learning environments might improve learning processes.

Conclusion

This paper discussed the automatic estimation of engagement in education/learning contexts during COVID-19 based on the emotional state of the students. This experiment leads to a clustering of the participants and helps to improve the practices in distance learning and enhance innovative learning. This work detailed the construction of the dataset used to train the engagement prediction model using CNN convolutional neural networks. Then the estimation of emotion prediction is conducted using a pre-trained model. Combining the two experiments leads to estimating each participant's clustering and deciding on their education. This work allowed us to answer these three research questions:

- RQ1: Proposed an automated model for measuring engagement.

- RQ2: How to propose a model to measure emotional state?

- RQ3: How to combine the models to group students and decide about each student?

In this study, an exploration was conducted on the various forms and degrees of engagement identified in existing research. An extensive examination was also performed on the emotions and their respective classifications. Moreover, comprehensive information was provided regarding the learning platform utilized throughout the COVID-19 pandemic. The obtained log files will be used to propose further findings and analysis.

Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for

re-publication, which is attached to the manuscript.
- Authors sign on ethical consideration's approval.
- Ethical Clearance: The project was approved by the local ethical committee in Ibn Tofaïl University, Kenitra, Morocco.

Authors' Contribution Statement

B A proposed the idea, collected data, and wrote the original draft, designing the manuscript's structure. A R then took charge of reviewing and editing the content, ensuring clarity and coherence while also carefully checking the language for accuracy. Building upon their efforts, Z S meticulously revised the article, paying close attention to the

references and carefully looking for any indications of plagiarism. As for the project's management and execution, Y E and A M played pivotal roles, as they skillfully identified and allocated resources, managed the team, coordinated various activities, and ultimately validated the project's success.

References

1. Berry LA, Kowal KB. Effect of Role-Play in Online Discussions on Student Engagement and Critical Thinking. Online Learn J 2022; 26(3): 4-21; https://doi.org/10.24059/olj.v26i3.3367.

2. Elshami W, Taha MH, Abdalla ME, Abuzaid M, Saravanan C, Al Kawas S. Factors that affect student engagement in online learning in health professions

education. Nurse Educ Today. 2022 Mar 1; 110: 105261; https://doi.org/10.1016/j.nedt.2021.105261.

3. Al-Sakkaf A, Omar M, Ahmad M. Social Worked-Examples Technique to Enhance Student Engagement in Program Visualization. Baghdad Sci J . 2019; 16(2): 0453; https://doi.org/10.21123/bsj.2019.16.2(SI).0453.

4. Alruwais N, Zakariah M. Student-Engagement Detection in Classroom Using Machine Learning Algorithm. Electronics .2023; 12(3): 731; https://doi.org/10.3390/electronics12030731.

5. Ali MM, Hassan N. Defining concepts of student engagement and factors contributing to their engagement in schools. Creat Educ. 2018 Oct 25; 9(14): 2161-70; https://doi.org/10.4236/ce.2018.914157.

6. Astin AW. Student involvement: A developmental theory for higher education. J Coll Stud Pers. 1984 Jul 25; 25(4): 297-308; https://psycnet.apa.org/record/1999-01418-006.

7. Chen Y, Zhou J, Gao Q, Gao J, Zhang W. MDNN: Predicting Student Engagement via Gaze Direction and Facial Expression in Collaborative Learning. CMES – Comput Model Eng Sci. 2023 Jul 1; 136(1): 381-401. https://doi.org/10.32604/cmes.2023.023234.

8. Maluenda-Albornoz J, Berríos-Riquelme J, Infante-Villagrán V, Lobos-Peña K. Perceived Social Support and Engagement in First-Year Students: The Mediating Role of Belonging during COVID-19. Sustainability. 2022 Dec 29; 15(1): 597; https://doi.org/10.3390/su15010597.

9. Tomaszewski W, Xiang N, Huang Y, Western M, McCourt B, McCarthy I. The Impact of Effective Teaching Practices on Academic Achievement When Mediated by Student Engagement: Evidence from Australian High Schools. Educ Sci. 2022 May 20; 12(5): 358; https://doi.org/10.3390/educsci12050358.

10. Ladino Nocua AC, Cruz Gonzalez JP, Castiblanco Jimenez IA, Gomez Acevedo JS, Marcolin F, Vezzetti E. Assessment of Cognitive Student Engagement Using Heart Rate Data in Distance Learning during COVID-19. Educ Sci. 2021 Sep 14; 11(9): 540; https://doi.org/10.3390/educsci11090540.

11. Gallinat A. Student engagement in the management of accelerated change. Learn Teach. 2018 Mar 1; 11(1): 35–56; https://doi.org/10.3167/latiss.2018.110103.

12. Coates H. A model of online and general campus-based student engagement. Assess Eval High Educ. 2007 Apr 1; 32(2): 121–41; https://doi.org/10.1080/02602930600801878.

13. Altuwairqi K, Jarraya SK, Allinjawi A, Hammami M. A new emotion–based affective model to detect student's engagement. J King Saud Univ Comput. 2021 Jan 1; 33(1): 99-109; https://doi.org/10.1016/j.jksuci.2018.12.008.

14. Schlechty PC. Engaging Students: The Next Level of Working on the Work. John Wiley & Sons; 2011. 224 p. 2011 Feb 16; https://www.wiley.com/en-gb/Engaging+Students%3A+The+Next+Level+of+Working+on+the+Work-p-9781118015520.

15. D'Mello S, Graesser A. Dynamics of affective states during complex learning. Learn Instr. 2012 Apr 1; 22(2): 145–57; https://doi.org/10.1016/j.learninstruc.2011.10.001.

16. Whitehill J, Serpell Z, Lin YC, Foster A, Movellan JR. The faces of engagement: Automatic recognition of student engagementfrom facial expressions. IEEE Trans. Affect Comput. .2014 Apr 10; 5(1): 86-98; https://doi.org/10.1109/TAFFC.2014.2316163.

17. Jang M, Park C, Yang HS, Kim JH, Cho YJ, Lee DW, et al. Building an automated engagement recognizer based on video analysis. ACM/IEEE Proc Int Conf Hum Robot Interact. 2014 Mar 3 (pp. 182-183). Bielefeld Germany. https://doi.org/10.1145/2559636.2563687

18. Li J, Ngai G, Leong HV, Chan SC. Multimodal human attention detection for reading from facial expression, eye gaze, and mouse dynamics. ACM SIGAPP Appl Comput Rev. 2016 Nov 4; 16(3): 37-49; https://doi.org/10.1145/3015297.3015301.

19. Monkaresi H, Bosch N, Calvo RA, D'Mello SK. Automated detection of engagement using video-based estimation of facial expressions and heart rate. IEEE Trans Affect Comput. 2016 Jan 6; 8(1): 15-28; https://doi.org/10.1109/TAFFC.2016.2515084.

20. Abdellaoui B, Moumen A, El Idrissi YE, Remaida A. Face detection to recognize students' emotion and their engagement: A systematic review. ICECOCS. 2020 Dec 2 (pp. 1-6). IEEE; https://doi.org/10.1109/ICECOCS50124.2020.9314600.

21. Kumari J, Rajesh R, Pooja KM. Facial expression recognition: A survey. Procedia Comput Sci. 2015 Jan 1; 58: 486-91; https://doi.org/10.1016/j.procs.2015.08.011

22. Omar MR, Husni H. Teen-Computer Interaction: Building a Conceptual Model with Thoughts-Emotion-Behaviour. Baghdad Sci J. 2019 Jun 20;16(2(SI): 0485; https://doi.org/10.21123/bsj.2019.16.2(SI).0485.

23. Mellouk W, Handouzi W. Facial emotion recognition using deep learning: review and insights. Procedia Comput Sci. 2020 Jan 1; 175: 689-94 ; https://doi.org/10.1016/j.procs.2020.07.101.

24. Villar BF, Viñas PF, Turiel JP, Marinero JC, Gordaliza A. Influence on the user's emotional state of the graphic complexity level in virtual therapies based on a robot-assisted neuro-rehabilitation platform. Comput Methods Programs Biomed. 2020 Jul 1; 190: 105359; https://doi.org/10.1016/j.cmpb.2020.105359.

25. Abdurrasyid A, Indrianto I, Susanti MN. Face detection and global positioning system on a walking aid for blind people. Bull Electr Eng Inform. 2022

Jun 1; 11(3): 1558-67; https://doi.org/10.11591/eei.v11i3.3429.

26. Henrie CR, Halverson LR, Graham CR. Measuring student engagement in technology-mediated learning: A review. Comput Educ. 2015 Dec 1; 90: 36-53; https://doi.org/10.1016/j.compedu.2015.09.005.

27. Karimah SN, Hasegawa S. Automatic engagement estimation in smart education/learning settings: a systematic review of engagement definitions, datasets, and methods. Smart Learn Environ. 2022 Dec; 9(1): 1-48; https://doi.org/10.1186/s40561-022-00212-y.

28. Shao M, Pham-Hung M, Alves SFDR, Snyder M, Eshaghi K, Benhabib B, et al. Long-Term Exercise Assistance: Group and One-on-One Interactions between a Social Robot and Seniors. Robotics. 2023 Jan 6; 12(1): 9; https://doi.org/10.3390/robotics12010009.

29. Thomas C, Sarma KP, Gajula SS, Jayagopi DB. Automatic prediction of presentation style and student engagement from videos. Comput Educ Artif Intell. 2022 Jan 1; 3: 100079; https://doi.org/10.1016/j.caeai.2022.100079.

30. Remaida A, Moumen A, El Idrissi YE, Abdellaoui B, Harraki Y. The use of personality tests as a pre-employment tool: A comparative study. InSHS Web of Conferences. SHS Web Conf. 2021; 119: 05007; https://doi.org/10.1051/shsconf/202111905007.

31. Sabri Z, FAKHRI Y, MOUMEN A. The Effects of Gamification on E-learning Education: Systematic Literature Review and Conceptual Model. Statistics. Optim Inf Comput. 2022 Feb 8; 10(1): 75-92; https://doi.org/10.19139/soic-2310-5070-1115.

32. Al-Fallooji AS, Al-Azawei A. Predicting Users' Personality on Social Media: A Comparative Study of Different Machine Learning Techniques. Karbala Int J Mod Sci. 2022; 8(4): 617-30; https://doi.org/10.33640/2405-609X.3262

33. Al-Shareeda MA, Manickam S. COVID-19 vehicle based on an efficient mutual authentication scheme for 5G-enabled vehicular fog computing. Int J Environ Res Public Health. 2022 Nov 24; 19(23): 15618; http://dx.doi.org/10.3390/ijerph192315618

34. Mejjad N, Cherif EK, Rodero A, Krawczyk DA, El Kharraz J, Moumen A, et al. Disposal Behavior of Used Masks during the COVID-19 Pandemic in the Moroccan Community: Potential Environmental Impact. Int J Environ Res Public Health. 2021 Apr 20;18(8):4382; https://doi.org/10.3390/ijerph18084382

35. Gloster AT, Lamnisos D, Lubenko J, Presti G, Squatrito V, Constantinou M, et al. Impact of COVID-19 pandemic on mental health: An international study. PloS one. 2020 Dec 31; 15(12): e0244809; https://doi.org/10.1371/journal.pone.0244809

36. Musolino S. Families, Relational Scenarios and Emotions in the Time of the COVID-19 Pandemic. Ital Sociol Rev. 2020 Dec 6; 10(3S): 737; https://doi.org/10.13136/isr.v10i3S.396

37. Matthewman S, Huppatz K. A sociology of Covid-19. J Sociol. 2020 Dec; 56(4): 675-83; https://doi.org/10.1177/1440783320939416

38. Mohammed BA, Al-Shareeda MA, Manickam S, Al-Mekhlafi ZG, Alreshidi A, Alazmi M, et al. FC-PA: Fog Computing-based Pseudonym Authentication Scheme in 5G-enabled Vehicular Networks. IEEE Access. 2023 Feb 22; 11: 18571-81. https://doi.org/10.1109/ACCESS.2023.3247222

39. Al-Mekhlafi ZG, Al-Shareeda MA, Manickam S, Mohammed BA, Qtaish A. Lattice-based lightweight quantum resistant scheme in 5G-enabled vehicular networks. Math. . 2023 Jan 12; 11(2): 399; https://dx.doi.org/10.3390/math11020399

40. Al-Shareeda MA, Manickam S. Man-in-the-middle attacks in mobile ad hoc networks (MANETs): Analysis and evaluation. Sym. 2022 Jul 27; 14(8): 1543; https://doi.org/10.3390/sym14081543

41. Singh AK, Srivastava S. Development and Validation of Student Engagement Scale in the Indian Context. Global Bus Rev 2014; 15(3): 505-515; https://doi.org/10.1177/0972150914535137

42. Gupta S, Kumar P, Tekchandani R. A multimodal facial cues based engagement detection system in e-learning context using deep learning approach. Multimed Tools Appl. 2023 Feb 10: 1-27; https://doi.org/10.1007/s11042-023-14392-3

43. Awais M, Raza M, Singh N, Bashir K, Manzoor U, Islam SU, et al. LSTM-based emotion detection using physiological signals: IoT framework for healthcare and distance learning in COVID-19. IEEE Internet Things J. 2020 Dec 10; 8(23): 16863-71; https://doi.org/10.1109/JIOT.2020.3044031

44. Thiruthuvanathan M, Krishnan B, Rangaswamy M. Engagement detection through facial emotional recognition using a shallow residual convolutional neural networks. Int J Intell Eng Syst. 2021 Mar 1; 14(2): 236-47; https://doi.org/10.22266/ijies2021.0430.21

45. Rodriguez P, Ortigosa A, Carro RM. Detecting and making use of emotions to enhance student motivation in e-learning environments. Int J Contin Eng Educ Life Long Learn. 2014 Jan 1; 24(2): 168-83; https://doi.org/10.1504/IJCEELL.2014.060156

اكتشاف المشاعر ومشاركة الطلاب في التعلم عن بعد أثناء الحجر الصحي بسبب كوفيد19

بنيوسف عبدالاوي[1]، أحمد رميدة[1] ، زينب صبري[2] ، يونس البوزكري الادريسي [1] ، أنيس مومن[1]

[1] مختبر العلوم الهندسية، المدرسة الوطنية للعلوم التطبيقية، جامعة ابن طفيل، القنيطرة، المغرب.
[2] كلية العلوم، مختبر علوم الحاسوب، جامعة ابن طفيل ، القنيطرة ، المغرب

الخلاصة

يعد التعلم عن بعد أحد أساليب التدريس والتعلم التي تم تبنيها بعد جائحة كوفيد 19. مهمة جذب ومعرفة اهتمام المتعلمين إلى الفصل صعبة على الأساتذة. في هذا البحث، قمنا بإنشاء آلية لتقدير مستويات مشاركة الطلاب ومعرفة احاسيسهم حيث نستخدم البيانات المرئية من مقاطع الفيديو المرسلة من طرف الطلاب المشاركين في دورات التعلم نظرًا لوجود العديد من الطرق لقياس مستويات مشاركة الطلاب. نقوم بمعالجة هذه الفيديوهات لتحديد مقدار مشاركة الطلاب واكتشاف عواطفهم. لقد قمنا بإنشاء نظامنا وتجريبه، الذي مكننا من تقييم انتباه الطلاب وتحديد عواطفهم. توضح النتائج أنه من الممكن قياس المشاركة ومعرفة المشاعر استغلالها في اتخاذ قرارات في صالح نتائج الطلاب وتحسين طرق التعليم والتعلم. يمكن تطبيق هذه التقنية في سيناريوهات أخرى، مثل القيادة الذاتية والأمان مع تعديل بسيط.

الكلمات المفتاحية: مشاركة الطلاب؛ كشف العاطفة؛ كوفيد -19؛ التعلم الإلكتروني؛ الدراسة عن بعد؛ الشبكات العصبية الملتفة.